Quality-Based Fusion in Multi-Biometric Systems

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Biometric Systems: Fact

- Biometric systems have non-zero error rates

	Test	Test Parameter	False Reject Rate	False Accept Rate
Fingerprint	FVC [2004]	20 years (average age)	2%	2%
	FpVTE [2003]	US govt. ops. Data	0.1%	1%
Face	FRVT [2002]	Varied lighting, outdoor/indoor	10%	1%
Voice	NIST [2004]	Text independent, multi-lingual	5-10%	2-5%

Sources of Error

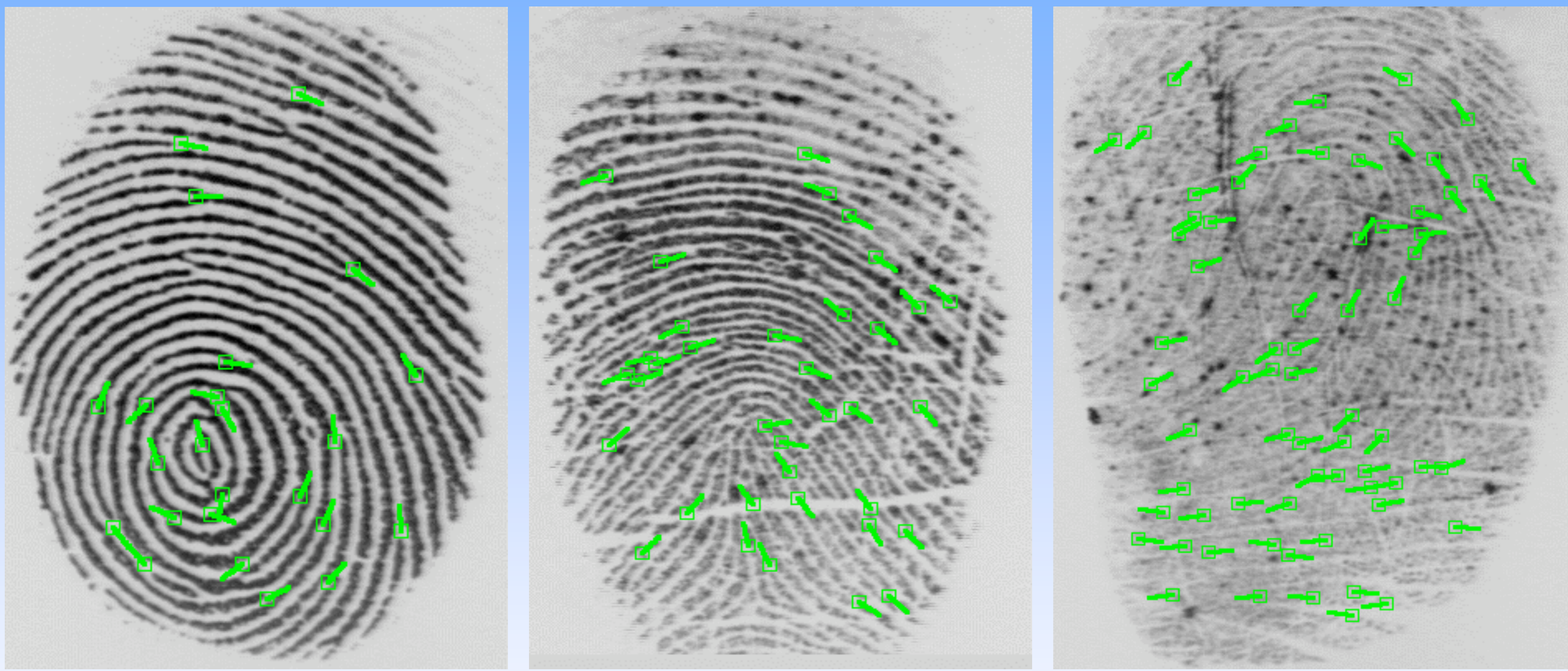
- Non-uniqueness of sensed biometric trait
- Artifacts in the biometric trait itself
- Sensor characteristics
- Sensing environment
- Limited discriminability in the feature set
- Non-robust matcher

How to Reduce Error Rates?

- Design new sensors & feature sets
- Enhance the sensed images
- Incorporate image quality in matcher
- Multibiometrics

We propose a Likelihood Ratio framework for biometric fusion that incorporates image quality

Noisy Images



Quality Index = 0.96
False Minutiae = 0

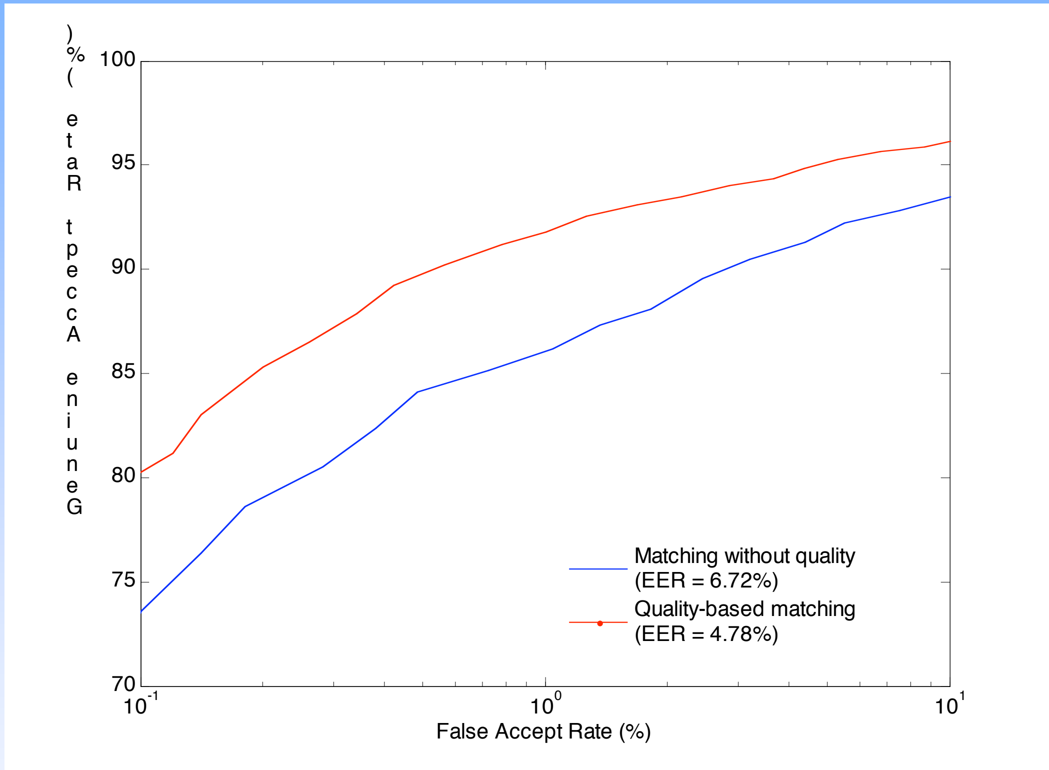
Quality Index = 0.53
False Minutiae = 7

Quality Index = 0.04
False Minutiae = 27

Global quality: to accept/reject enrolled/query image

Local quality: to assign weights to local regions

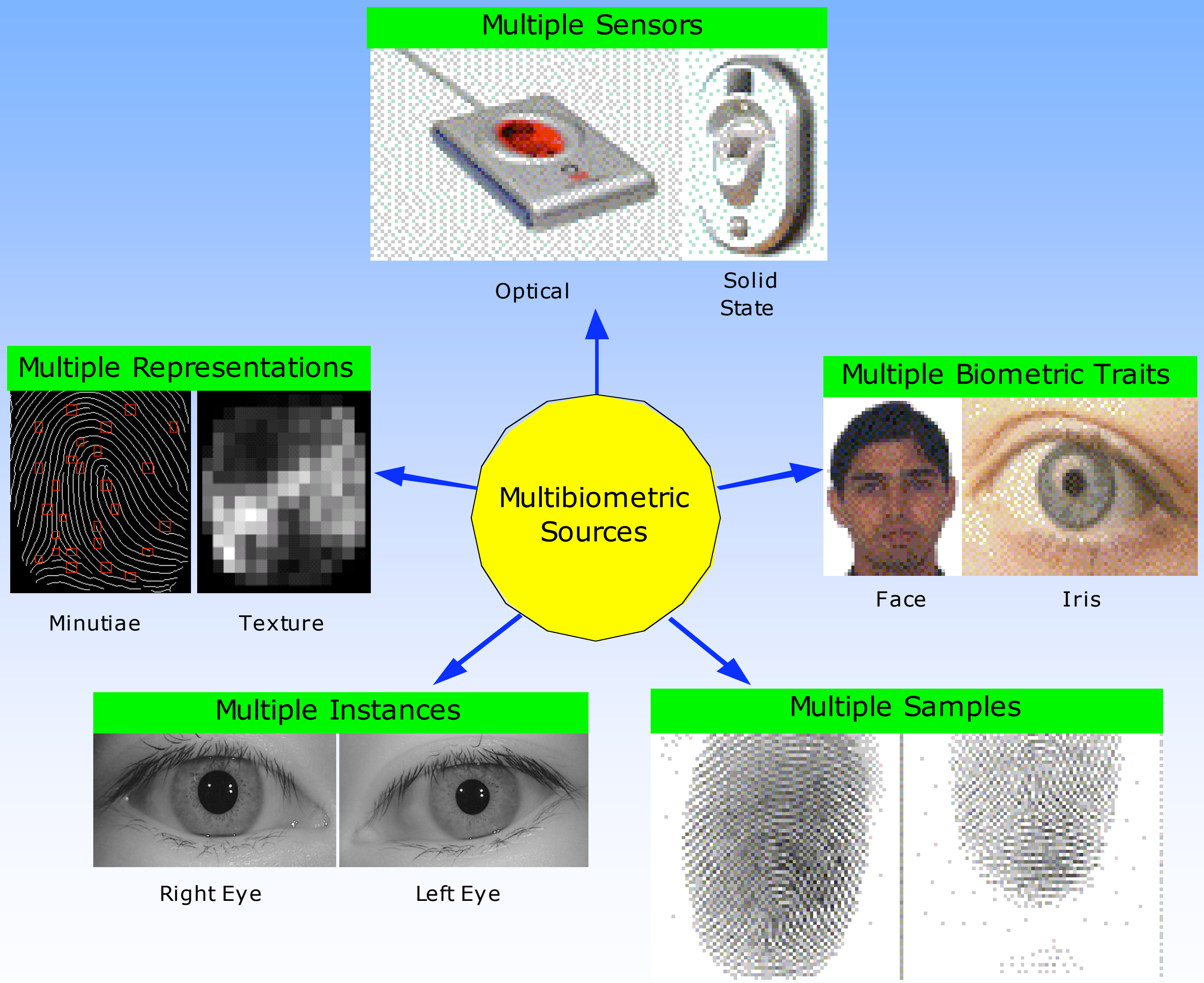
Utilizing Image Quality in Matching



Weigh fingerprint minutiae correspondences based on their quality

Y. Chen, S. Dass and A. Jain, "Fingerprint Quality Indices for Predicting Authentication Performance", *Proc. of AVBPA*, pp. 160-170, Rye Brook, NY, July 2005

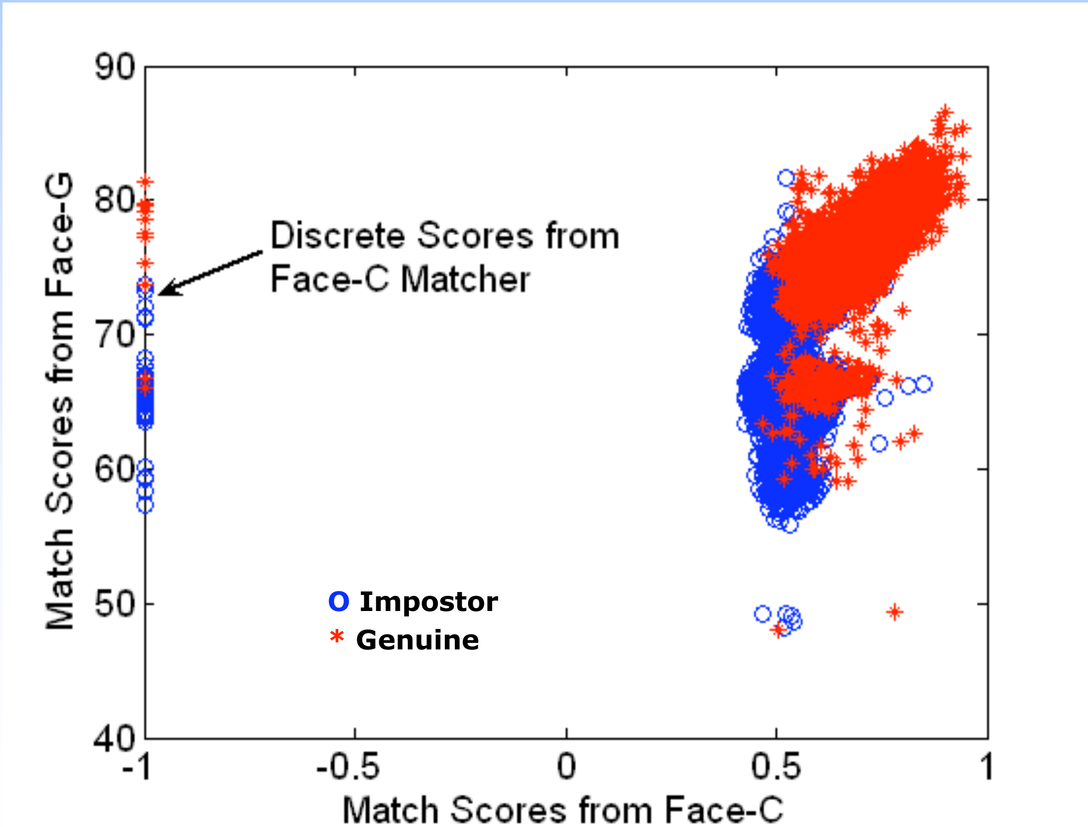
Multibiometrics



A. Ross, K. Nandakumar and A. K. Jain, Handbook of Multibiometrics, Springer, 2006

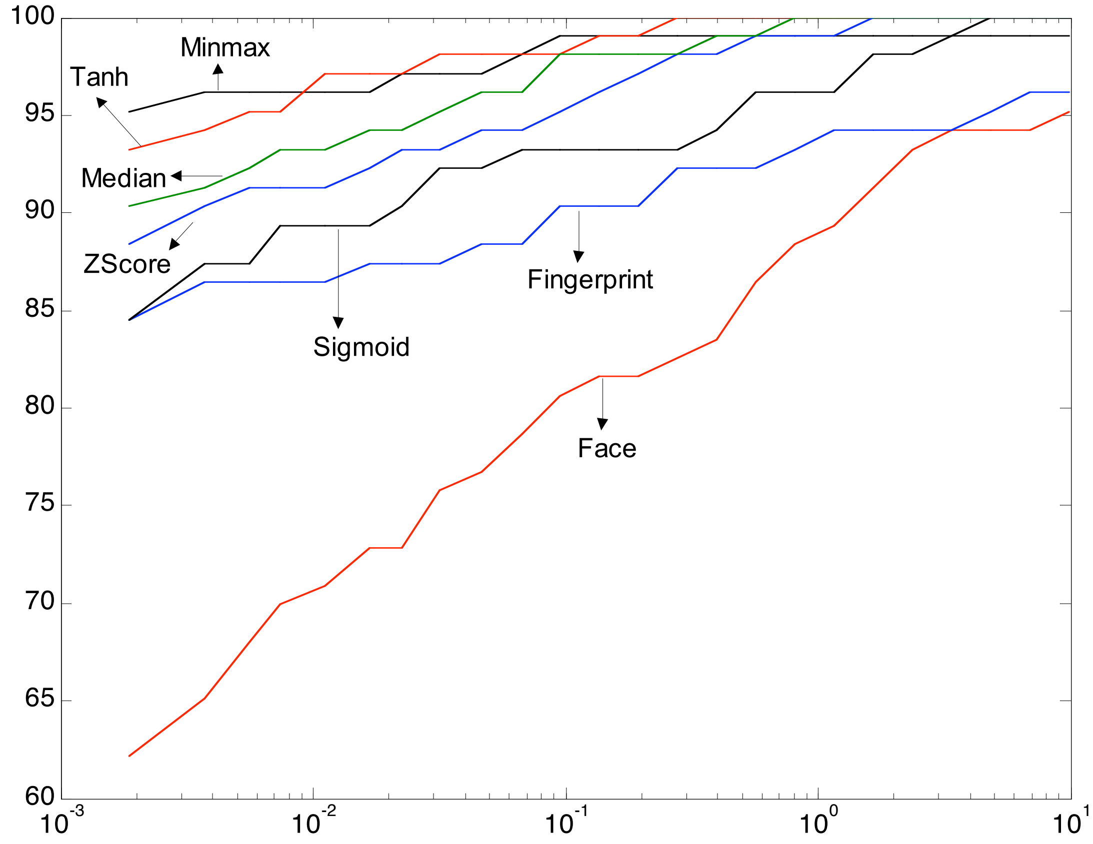
Match Score Fusion

- Score ranges are different; C: [-1,1], G: [0,100]
- Statistical distributions are different. In addition, they have continuous and discrete components
- Scores from the matchers are correlated



Match scores from the two face matchers in NIST-BSSR1 database

Which Fusion Method?



Match scores from face and fingerprint matchers from NIST-BSSR1 database are normalized using different techniques and are combined using sum rule

Likelihood Ratio Based Fusion

- Neyman-Pearson theorem: For a given FAR, the likelihood ratio test provides the maximum GAR
- Let ***S*** be the match score vector, ***S*** = (S_1, S_2, …, S_K) for K different matchers. Likelihood ratio (LR) test is
  - Decide "genuine" if

$$FS(\boldsymbol{S}) = \frac{P(\boldsymbol{S} \mid genuine)}{P(\boldsymbol{S} \mid impostor)} \geq \eta$$

where η is determined by the given FAR

- If K matchers are independent, LR test is simplified as

$$PFS(\boldsymbol{S}) = \prod_{k=1}^{K} \frac{P(S_k \mid genuine)}{P(S_k \mid impostor)} \geq \eta$$

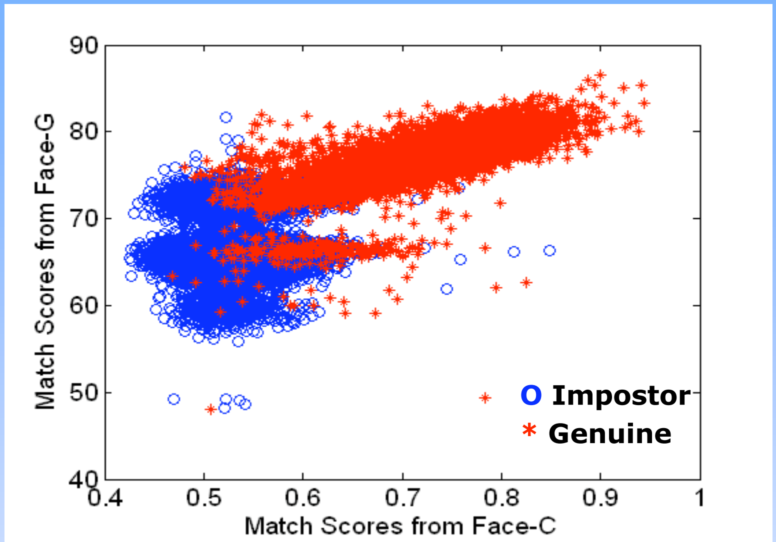
This decision rule is known as product fusion

Density Estimation

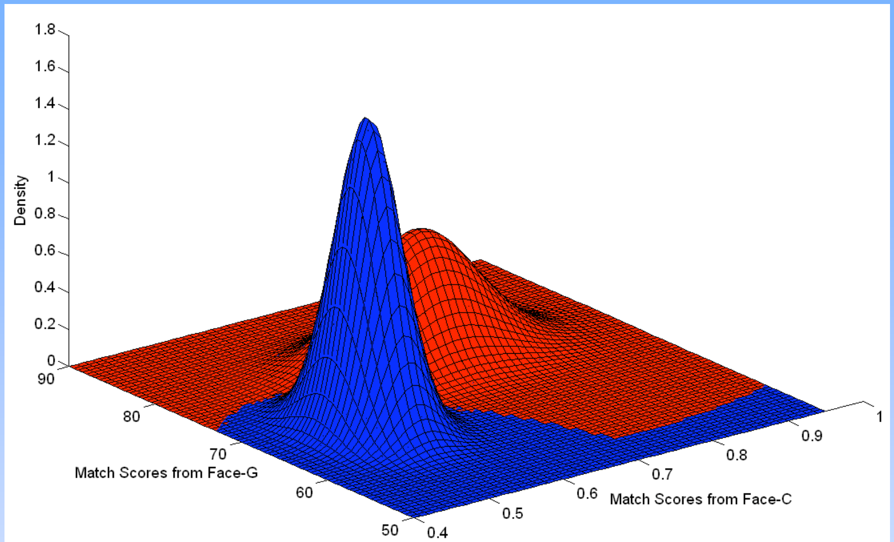
- Gaussian assumption is not reasonable
- Match scores may have discrete components
- We propose generalized densities - a mixture of continuous and discrete components
- Detect discrete components first; estimate the continuous portion using kernel density technique
- Correlation between matchers is modeled using multivariate copula function

S. Dass, K. Nandakumar and A. Jain, "A Principled Approach to Score Level Fusion in Multimodal Biometric Systems", *Proc. of AVBPA,* pp. 1049-1058, Rye Brook, NY, July 2005

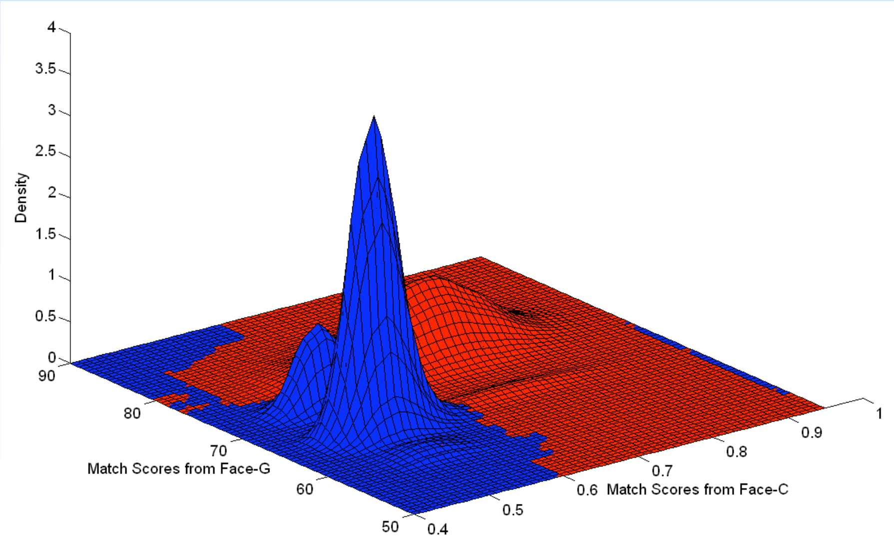
Joint Density Estimates



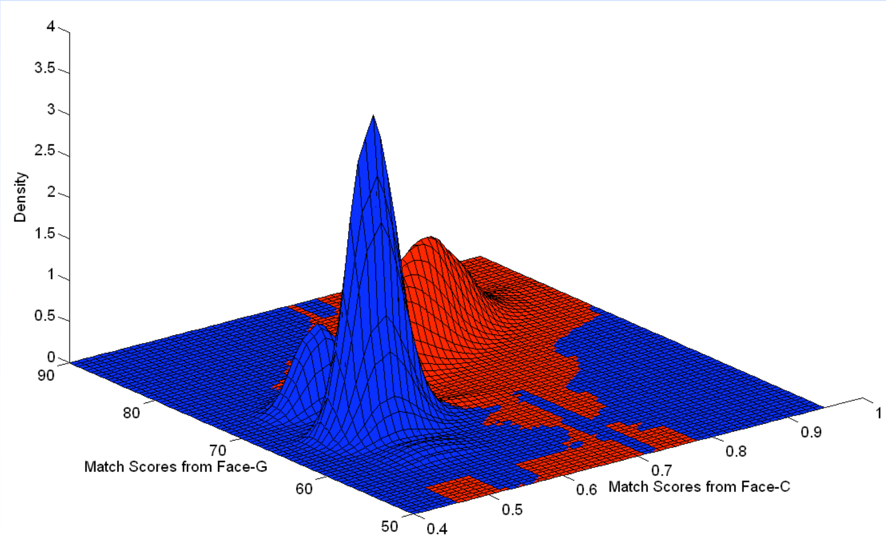
Scatter plot of data



Parametric (Gaussian) (assuming independence)



Non-parametric (assuming independence)



Non-parametric (using copulas)

Quality-based Fusion

- Estimate joint density of match score and image quality to assign weights to individual matchers
- Let $\boldsymbol{Q} = (Q_1, Q_2, \ldots, Q_K)$ be the quality vector associated with the K-dimensional match vector
- Quality-based fusion (QF) rule decides "genuine" if

$$QFS(\boldsymbol{S},\boldsymbol{Q}) = \frac{P(\boldsymbol{S},\boldsymbol{Q} \mid genuine)}{P(\boldsymbol{S},\boldsymbol{Q} \mid impostor)} \geq \eta$$

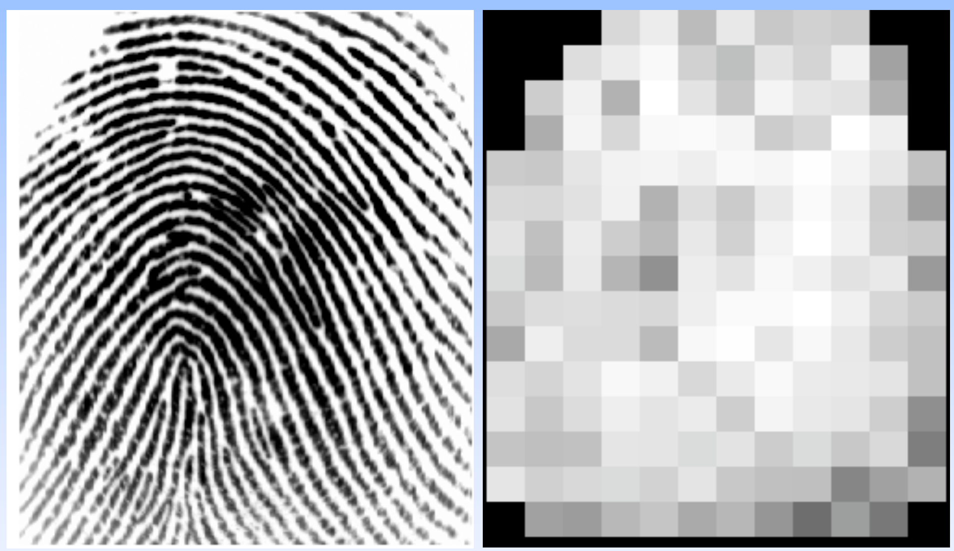
- If K matchers are independent, the QF rule is simplified as

$$QPFS(\boldsymbol{S},\boldsymbol{Q}) = \prod_{k=1}^{K} \frac{P(S_k, Q_k \mid genuine)}{P(S_k, Q_k \mid impostor)} \geq \eta$$

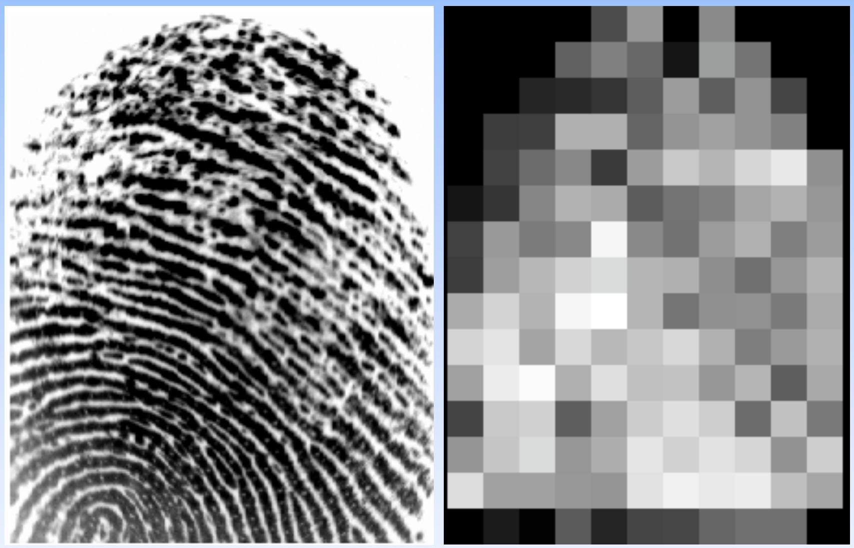
This decision rule is known as quality-based product fusion

Fingerprint Quality

- Partition the image into blocks and estimate local quality* (γ), $0 \leq \gamma \leq 1$



Quality map for a good image



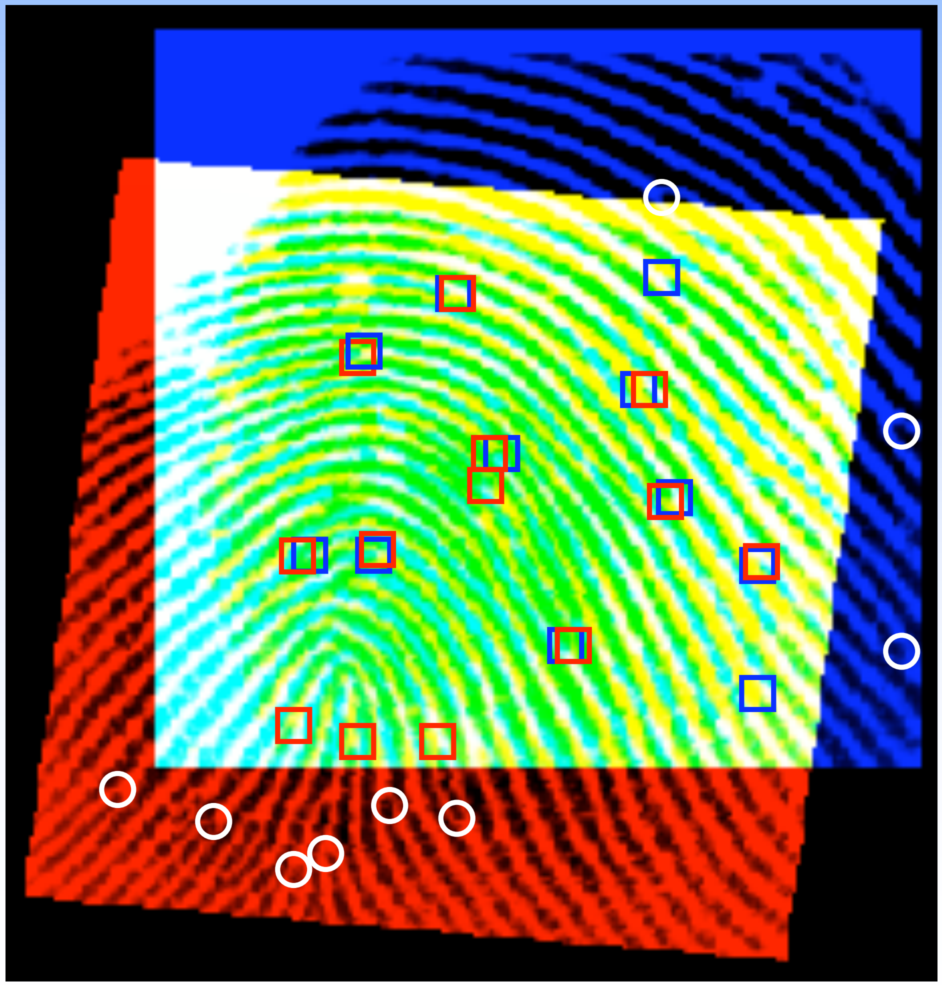
Quality map for a poor image

Note: Brighter pixels indicate better quality

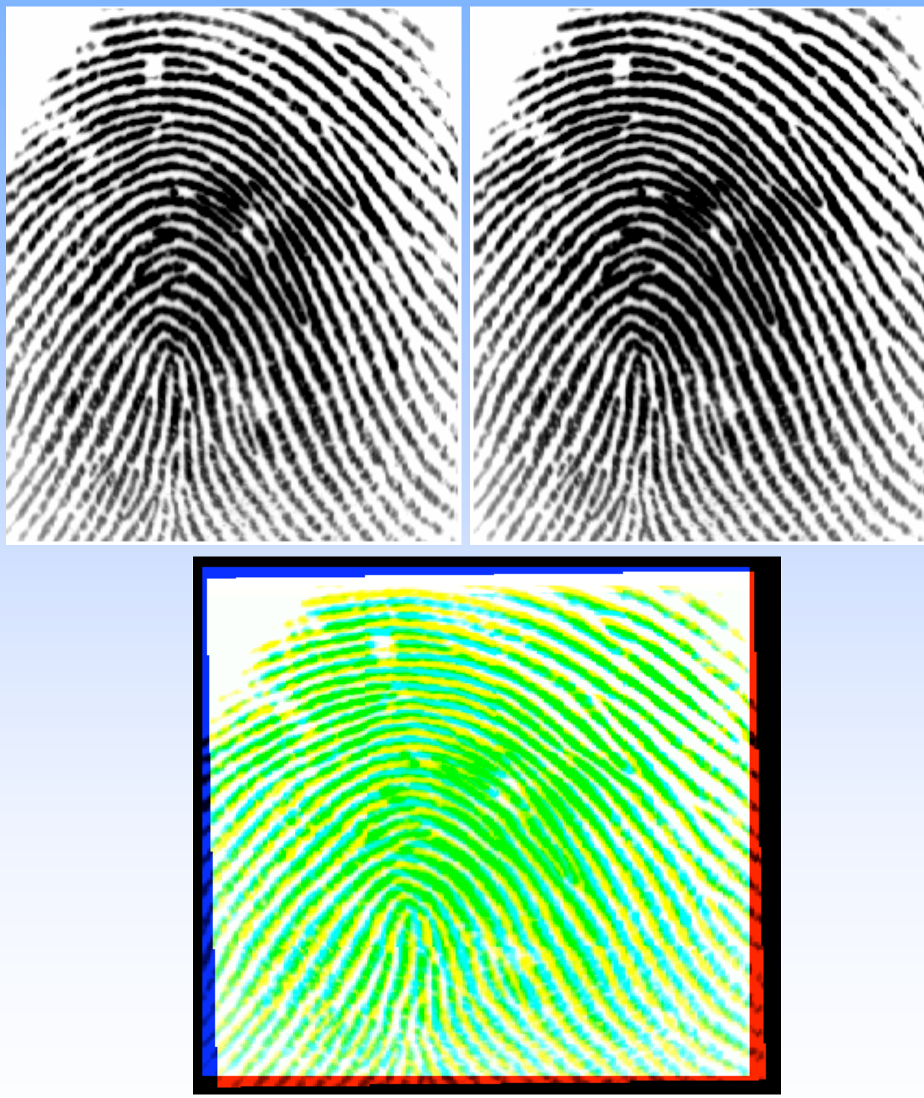
* Y. Chen, S. Dass and A. Jain, "Fingerprint Quality Indices for Predicting Authentication Performance", *Proc. of AVBPA*, pp. 160-170, Rye Brook, NY, July 2005

Pair-wise Fingerprint Quality

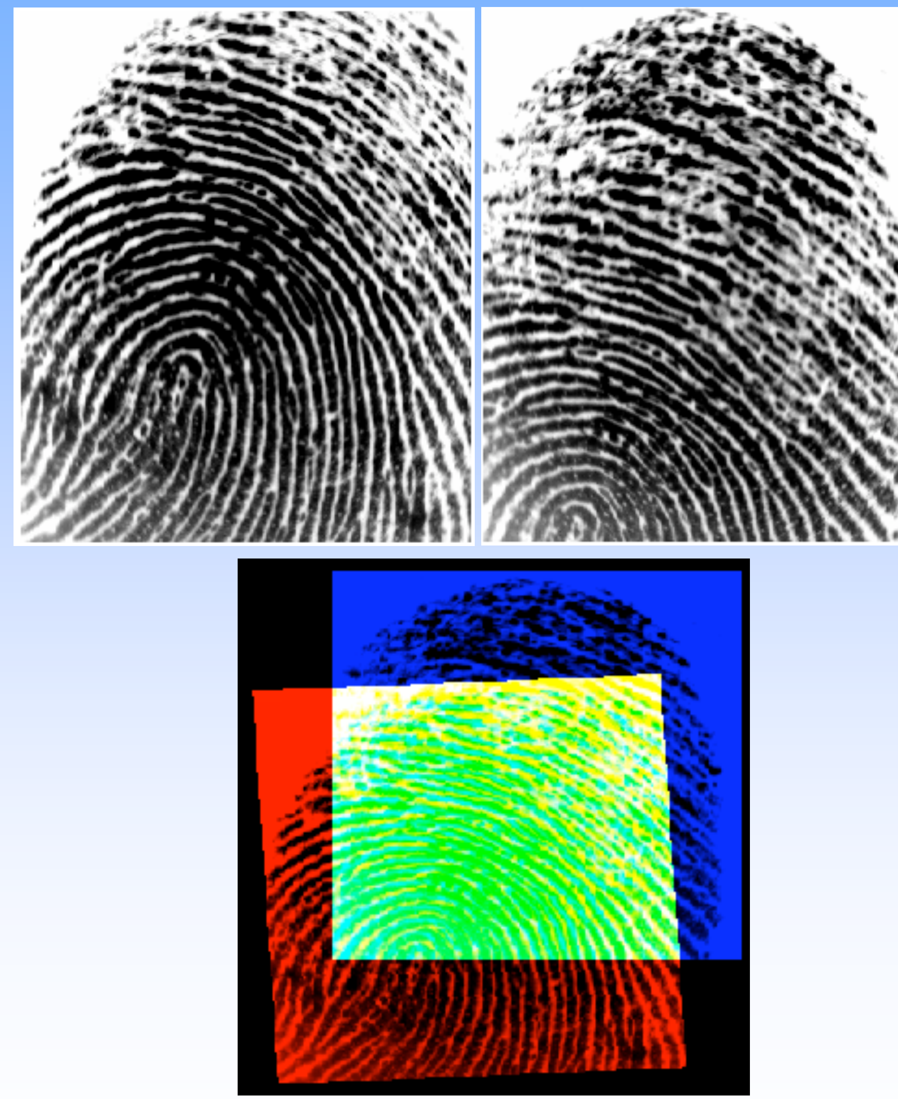
Pair-wise quality depends on the quality of minutiae in the overlapping region and the area of overlap



Fingerprint Quality Examples



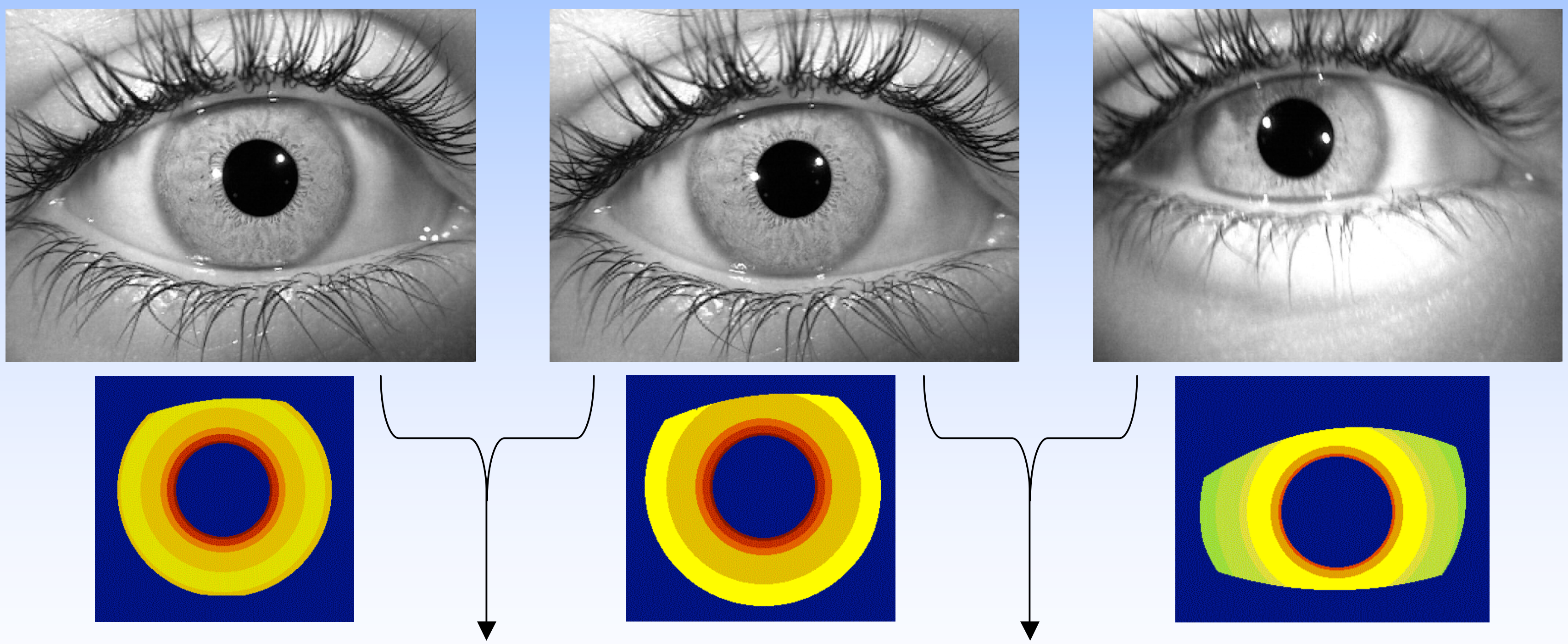
Good quality pair (Q_{finger}=0.90)



Poor quality pair (Q_{finger}=0.28)

Pair-wise Iris Quality

- Iris local quality* is defined using 2-D wavelet transform in local windows
- Correlation of local quality vectors of template and query is defined as the quality of the pair

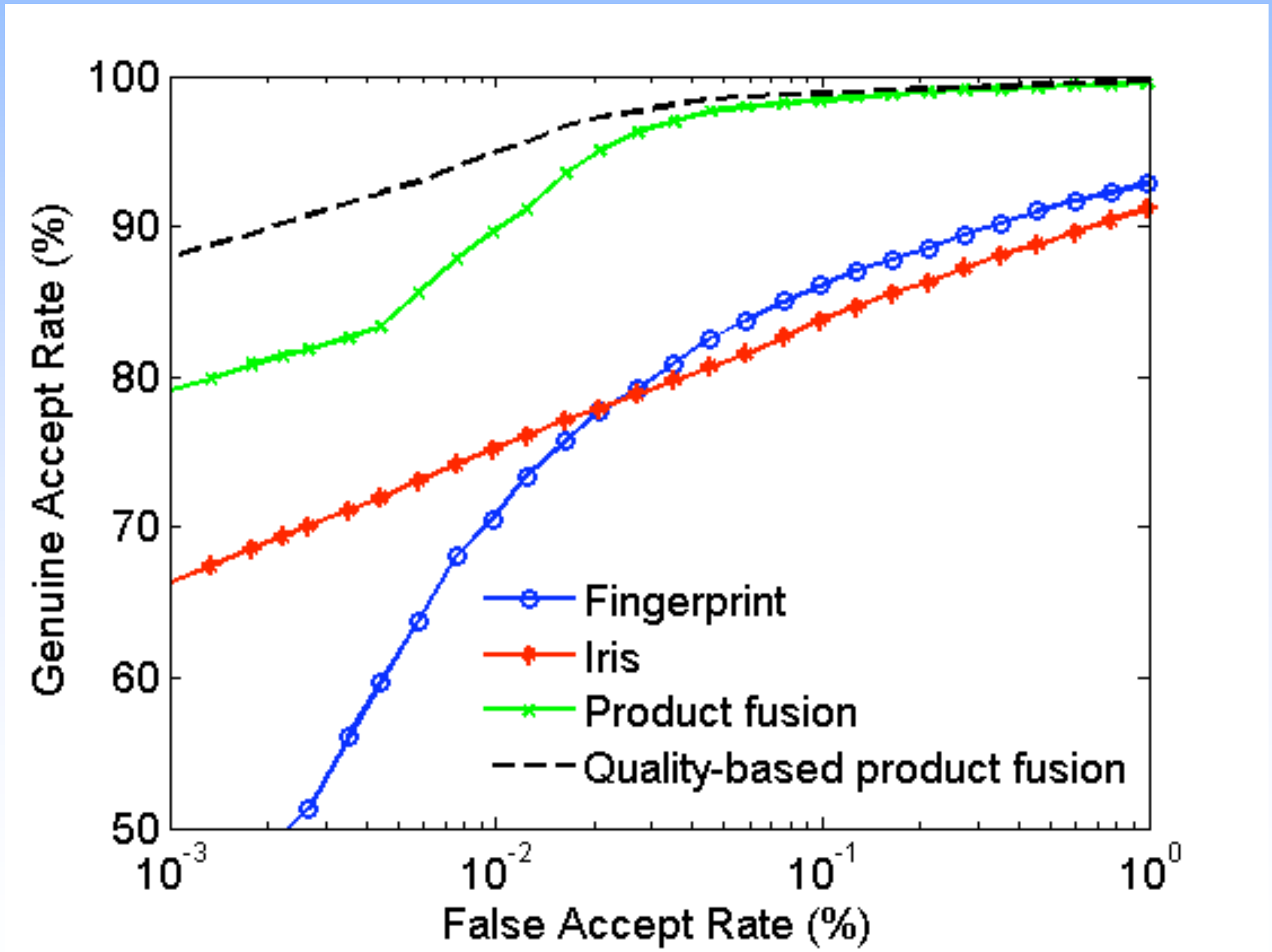


Good quality pair (Q_{iris}=0.80) Poor quality pair (Q_{iris}=0.42)

* Y. Chen, S. Dass and A. Jain, "Localized Iris Image Quality Using 2-D Wavelets", Proc. of ICB, pp. 373-381, Hong Kong, Jan. 2006

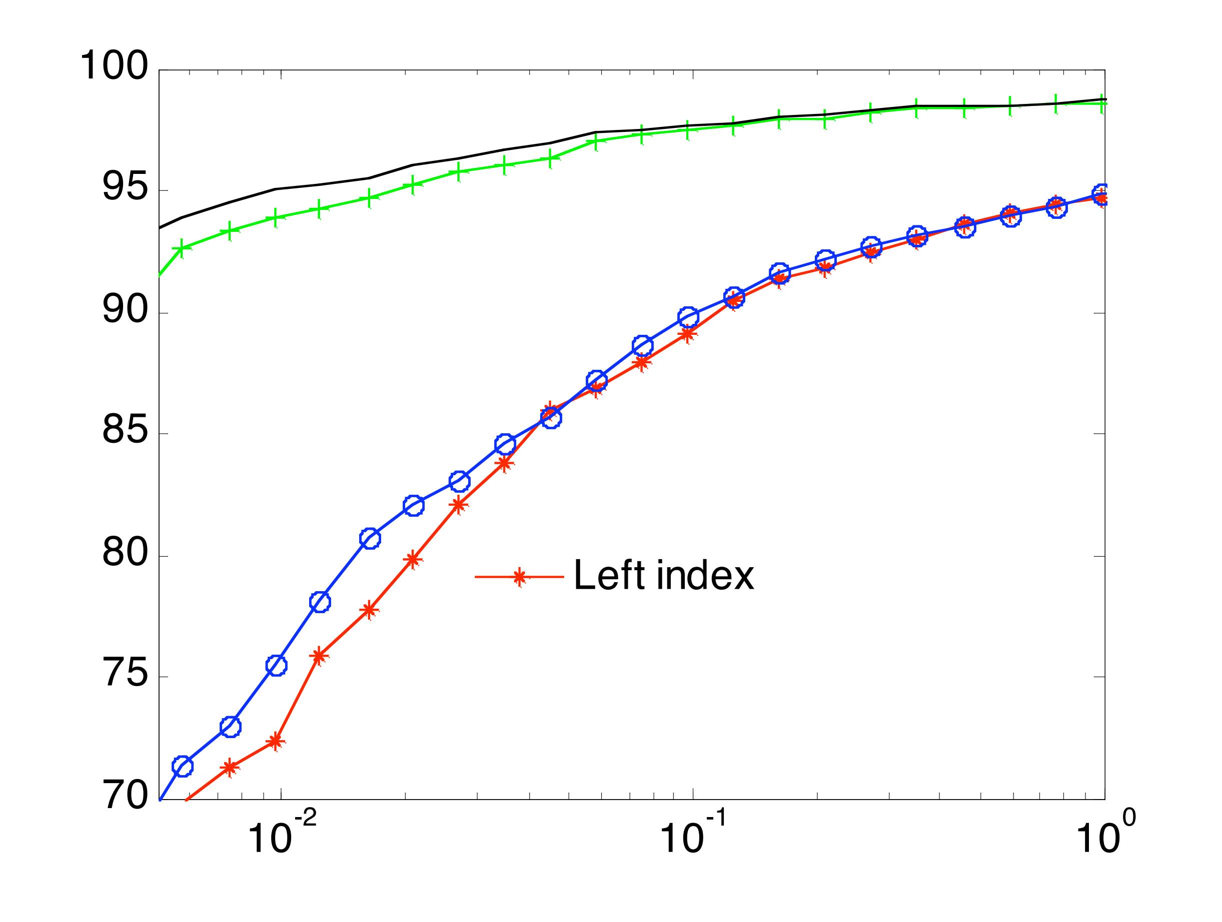
Fusion of Fingerprint and Iris

- WVU joint multimodal database; 320 subjects, 5 samples/modality/subject; 20-fold cross-validation



Fusion of Two Fingers

- 247 subjects, 5 impressions/finger/subject



Introducing quality here makes only a small improvement because unlike finger and iris, quality values of the 2 fingers from the same subject are correlated

Summary

- Two main sources of observed error in biometric systems are
  - Image quality
  - Non-uniqueness of sensed biometric trait
- We have proposed a likelihood ratio framework to combine multiple matchers and image quality
- Need for large public domain multibiometric databases that also include quality values